Asian Journal of Water, Environment and Pollution, Vol. 16, No. 2 (2019), pp. 43–50.
DOI 10.3233/AJW190018

CSO Technique for Solving the Economic Dispatch Problem Considering the Environmental Constraints

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Received January 25 2019; revised and accepted March 1, 2019

Abstract: In this paper, the competitive swarm optimization (CSO) algorithm is applied for handling the economical load dispatch problem. The CSO algorithm is fundamentally encouraged by the particle swarm optimization (PSO) algorithm, but it does not memorize the personal best and global best to update the swarms. Rather in CSO algorithm, a pairwise competitive scenario was presented, where the loser particle is updated from the winner particle and the winner particles are directly accepted to the next population. The algorithm has been performed to find the generations of different units in a plant to reduce the entire fuel price and to maintain the total demand as well as the losses. The experimental study and investigations have revealed better performance for the CSO algorithm than the PSO and numerous state-of-art meta-heuristic algorithms in solving the economical power dispatch problem.

Key words: Load dispatch problem, competitive swarm optimization, computational intelligence.

Introduction

Electric power with large interconnection of network, is considered as one of the global crisis. The primary reason behind the situation is due to its continuous increase in cost. Therefore, it is much essential to decrease the prices of electric power. This largely depends on the significant reduction in the amount of fuel consumption and functioning charge of the electric power plant. So, primary goal of an electric power plant is to provide high quality electric energy with lowest possible cost while satisfying different limits and constraints. These limits and constraints in the power plant formulated as the economic load dispatch (ELD) problem (Chowdhury and Rahman, 1990; Bakirtzis et al., 1994; Gaing, 2003; Sinha et al., 2003; Danaraj and Gajendran, 2005; Yang et al., 2012).

These problems are highly non-smooth and non-linear due to different scenarios such as input-output values of the generators, capacity of generators and the environmental conditions. Conventionally, the load dispatch problem may be handled by numerous traditional approaches, such as the participation factors approach (Chowdhury and Rahman, 1990), the interior point approach (Granville et al., 1994), the gradient based approach (Dhar and Mukherjee, 1973), and the dynamical programming approach (Liang and Glover, 1992; Shoultsa et al., 1996). Still, the stated approaches fail to work efficiently for non-smooth and non-convex functions. Therefore, to efficiently handle these difficulties of real-world power systems, a varied

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range of non-traditional optimization approaches have been engaged to handle the load dispatch problems. The evolutionary algorithms is such type of approaches that solve this non-smooth, non-convex and non-linear ED problem very competently and frequently attain good solutions. These approaches comprise of genetic algorithms (Chen and Chang, 1995; Chiang, 2005), particle swarm optimization (Gaing, 2003; Yao, 2012; Mishra, 2012), differential evolution (Vanitha and Thanushkodi, 2011; Coelho and Mariani, 2006; Elsayed et al., 2013) and evolutionary programming (Park et al., 1998; Sinha et al., 2003). In this paper, an innovative variation of the PSO algorithm, called competitive swarm optimizer (CSO) (Mohapatra et al., 2017; Cheng and Jin, 2014; Mohapatra et al., 2019) is used to handle the ED problems. The CSO algorithm is basically motivated from the PSO algorithm but theoretically quite dissimilar. In CSO, the personal best position and the global best position do not participate in modernizing the particles. Moreover, a pairwise competitive technique was presented and the loser particle is modernized by educating after the winner particle. Implementation of CSO algorithm is not only easy but also it has a consistent result. The paper is prepared first with the introduction to the ED problem and the CSO approach. Then the formulation and implementation of the CSO in solving ED problems is presented. Finally, the discussion to the experimental results on six power systems and the conclusion is drawn.

The Economic Dispatch Problem

Problem Definition

The prime factors influencing generation of power in a power plant are cost of fuel, operating efficiencies of power generators, and the losses due to transmission. The whole expenditure of power creation can be defined as a function of the individual generators that intake in particular restrictions. So, the objective is to find the perfect mixture of generation of altogether plants in directive to reduce the whole operating cost. In each case, the i^{th} generator fuel cost is characterized as a function of the actual generated power.

$$F_i(p_i) = u_i \times p_i^2 + v_i \times p_i + w_i$$

where F_i is the i^{th} generator cost of and u_i, v_i and w_i are the coefficients cost of i^{th} generator. The power of i^{th} generator is given by p_i and the total generators number is given by N.

Constraint for Power Balance

In general, the total generated power through the generators essentially meet the demand and the total transmission line loss. Hence, the following equality constraints should be satisfied.

$$p_d + p_l = \sum_{i=1}^{N} p_i$$

Here, p_d represents the demand and p_l represents the total line transmission loss. This transmission loss is computed by applying the Kron's formula as follows:

$$p_l = \sum_{i=0}^{N} \sum_{j=1}^{N} p_i B_{ij} p_{ij} + \sum_{i=1}^{N} B_{i0} p_i + B_{00}$$

Here, the B terms B_{ij}, B_{i0} and B_{00} are known as the loss coefficients.

Generator Constraint

The entire power produced from the generators are bounded by the maximum active power $p_{\max}$ and the minimum power $p_{\min}$ respectively due to the capabilities and constraints on the generators. Therefore, the following condition must be satisfied for each generator.

$$p_{min} \le p_i \le p_{max}$$

Limits of Ramp Rate Constraint

In actual functioning, procedure of the generators, the working limit of entirely divisions is regulated with the following ramp rate:

(a) if power generation rises

$$p_i - p_i^0 \le PR_i$$

(b) if power generation falls

$$p_i^0 - p_i \le QR_i$$

Here, p_i^0 is the earlier produced power, PR_i is up ramp range of the i^{th} unit; and QR_i is the down-ramp boundary of the i^{th} generator.

Transmission Line Flow Constraints

The transmission line flow should be satisfied by the following inequality constraint.

$$p_{fk} \le p_{fkmax}$$

Here, p_{fk} the actual power of k^{th} line, whereas f signifies the total transmission lines and p_{fkmax} is the maximum loading capability of the p^{th} line.

Competitive Swarm Optimizer

The Competitive Swarm Optimizer (CSO) approach was initially suggested by Cheng and Jin (2014) as a population-centered optimization technique which was inspired from the collective activities of fishes, honey bees and bird herds. In recent times, CSO has been established as one of the effective technique due to its success in acting challenging optimization tasks in very simple way. The algorithm was primarily encouraged from the PSO algorithm but it is practically very much different. It reports the scenario of premature convergence by completely getting rid of global best and personal best terminologies. Hence, in CSO, the personal best and the global best positions are not participated in modernizing the particles. The concept of competition technique between particles was first introduced by Liang et al. (2006) without the global best position. Later, the similar concept was prepared in a multi swarm structure (Cheng et al., 2013). Subsequent to this idea, CSO discovered the practice of the competitive mechanism among the particles in one sole swarm. In CSO, the particle fails a competition learns from the winner as a replacement for global best and particle best position. As the chief driving strength after this notion is the pairwise competition technique among different particles in the swarm, the algorithm was named as Competitive Swarm Optimizer (CSO).

Motivation and Proposition

In Competitive Swarm Optimizer, only 50% of the particles are modernized in every iteration. Therefore the 50% particles migrate in the direction of the better solutions which results in a higher rate of convergence. The rest half of the swarms are passed to the next generation. Consequently, the presence of good diversity in the swarm is ensured. The inspiration for the partition of the whole swarm into two swarms is for the fast convergence. The two-population notion in CSO permits 50% of the population to update. Hence half of the swarms are congregating towards the decent solutions. The competition scheme of the CSO and the up-gradations of the particles is presented in Figure 1.

Let us consider the minimization problem as *minf* = $f(x)$ such that $x \in X$. Here $X \in R^n$ is the solution space and n represents the measurement of the region. The problem is resolved by arbitrarily adjusting a swarm $Q(s)$ containing p particles at generation s. Here p is recognized as the size of the swarm. The n dimensional position of every particle is given by $x_i(s) = (x_{i,1}(s), x_{i,2}(s), \ldots, x_{i,n}(s))$, whereas the n dimensional

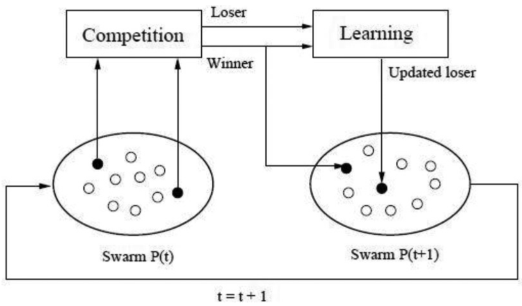

Figure 1: Swarm's competitive scenario in CSO and the upgradation process.

velocity vector is given by $v_i(s) = (v_{i,1}(s), v_{i,2}(s), \ldots, v_{i,n}(s))$. In each iteration, the particles in $Q(s)$ are randomly divided into two different groups, and are allocated into $p/2$ pairs. Afterwards, a competition is created among the particles in every pair and as a consequence of the struggle, the particle with best fitness value, represented as winner, is moved straight to the subsequent generation $Q(s+1)$ whereas the particles that fails the race are represented as loser. The losers modernize by inspiring from the winner particle and the overall mean position. The position and velocity of the winners and losers in the t-th round of competition in generation s is represented as $x_w(s)$, $x_l(s)$ and $v_w(s)$ and $v_l(s)$ respectively, and the value of t varies in between 1 to $\frac{p}{2}$. Hence, afterward the t-th round competition, the losers' velocity is modernized by the resulting approach as follows:

$$v_{l,k}(s+1) = R_1(t,s)v_{l,t}(s) + R_2(t,s)\left(x_{w,t}(s) - x_{l,t}(s)\right) + \varphi_1 R_3(t,s)\left(\overline{x_t(s)} - x_{l,t}(s)\right) \quad (1)$$

The position of the loser is rationalized with the new velocity as follows:

$$x_{l,t}(s+1) = x_{l,t}(s) + v_{l,t}(s+1) \quad (2)$$

Here, $R_1(t,s), R_2(t,s)$, and $R_3(t,s)\,\varepsilon[0,1]^n$ are randomly created after the t-th round competition in s-th geeration. $x_t(s)$ is known as the mean position, φ_1 is the factor that wheels the effect of $x(s)$. The algorithm of the CSO procedure is precised in Algorithm 1.

Algorithm 1: The pseudo-code of the CSO algorithm.

Now, s denotes a group of particles. At each generation 's', $Q(s)$ signifies the whole swarm. Likewise $X_w(s)$ and $X_l(s)$ symbolizes winner and loser swarm individually. The *terminal condition* is given by entire fitness function.

1. $s = 0$;

2. Initialize arbitrarily the swarm $Q(0)$;
3. **Do while** *terminal condition* is not fulfilled;
4. Calculate the fitness of each particle in $Q(s)$;
5. $S = Q(s)$, $Q(s + 1) = \emptyset$;
6. **Do while** $S \neq \emptyset$;
7. Select randomly two particles $X_1(s)$ and $X_2(s)$ from S; s. t. $f(X_1(s)) \leq f(X_2(s))$
8. Assign $X_w(s) = X_1(s)$ and $X_l(s) = X_2(s)$;
9. Add $X_w(s)$ into $Q(s + 1)$;
10. Update $X_l(s)$ to $X_l(s + 1)$ by Eqns. (*1-2*) and add to $Q(s + 1)$;
11. Remove $X_1(s)$, $X_2(s)$ from S;
12. **End**
13. $s = s + 1$;
14. **End**

Problem Formulation and Implementation

Formulation

Let F_i represents the cost of generating energy in the i^{th} generator. Then the total cost C is defined as $\Sigma_{i=1}^{N} F_i$. The actual generated power p_i has a prime effect on the cost function. Therefore, the separate cost F_i of the generator units is measured a function only of p_i. Hence, the total cost C can be written as $\Sigma_{i=1}^{N} F_i(p_i)$. The key goal of the Economic Load Dispatch problem is to reduce the whole expenditure C.

$$\text{Minimum} \quad C = \Sigma_{i=1}^{N} F_i(p_i)$$

$$\text{Subject to} \quad \Sigma_{i=1}^{N} p_i = p_d + p_l$$

Implementation

1. Specify the ranges of power capacity of every generating unit, maximum number of iterations, the transmission loss coefficient B, population size and the parameter φ_1.
2. Initialize randomly the entities of the population for all units in the specified range.
3. For every distinct individual of the population, calculate the loss coefficients B.
4. Calculate the evaluation function F_i of each generating unit p_i
5. Select winners and loser in each pair through competition mechanism for all individuals of the population.
6. Update the position and the velocity of every loser individual agreeing to Eqns. (1) and (2).
7. Find the best evaluation value among the population as the global best solution.
8. If the total of iteration does not reach the extreme then go to step 3 otherwise end.
9. The single that produce the newest overall best is identified as the best generation power for each unit.

Results and Analysis

The diagram of an IEEE-30 system with six generators is given in Figure 2. Here, the cost coefficients (u_i, v_i and w_i) and the limit restrictions (p_{imin}, p_{imax}) of the generators are provided in Table 1. The coefficient matrix B of the given system is given in Table 2. CSO is applied to handle the presented problem for finding the economical load dispatch of various different loads of 585 mega Watts, 600 mega Watts, 700 mega Watts, 800 mega Watts, 1000 mega Watts and 1200 mega Watts. The optimum generated power for different above demands together with the minimum fuel cost and power loss for the given system using CSO are shown in Table 3. For comparison with CSO, different popular algorithms such as lambda iteration (Chowdhury and Rahman, 1990) and quadratic programming (Danaraj and Gajendran, 2005), GA (Bakirtzis et al., 1994) and PSO (Gaing, 2003; Karthik and Reddy, 2014) are taken into consideration.

The comparison results of the algorithms is provided in Tables 4, 5 and 6 for demands as 600 MW, 700 MW and 800 MW respectively. Figure 3 represents the

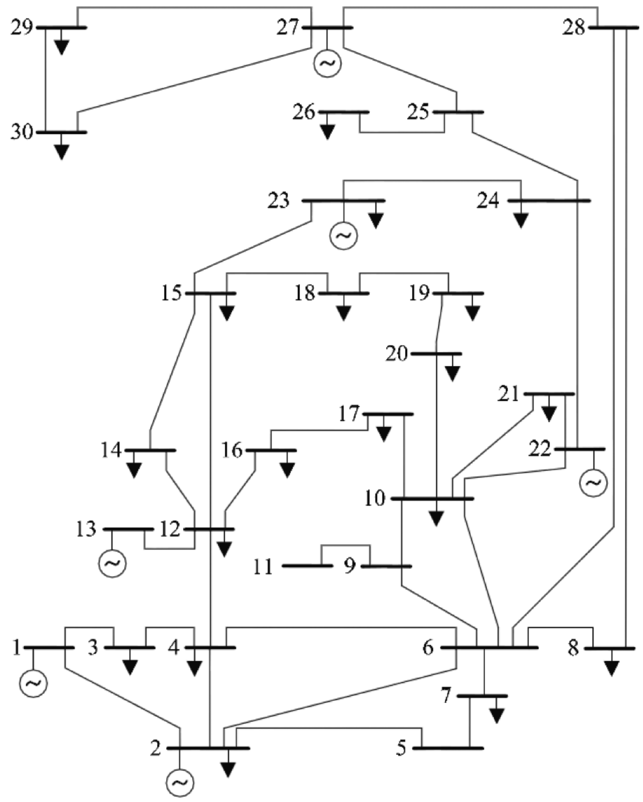

Figure 2: A 30 bus IEEE system.

Table 1: The cost coefficients with the limits of the generators

No.	u_i	v_i	w_i	p_{imin}	p_{imax}
1	0.15240	38.53973	756.79886	10	125
2	0.10587	46.39655	451.32513	10	150
3	0.02803	40.39655	1049.9977	35	225
4	0.03546	38.32782	1243.5311	35	210
5	0.02111	36.32782	1658.5596	130	325
6	0.01799	38.27041	1356.6592	125	315

Table 2: Loss coefficient matrix B

[0.000140	0.000017	0.000015	0.000019	0.000026	0.000022
0.000017	0.000060	0.000013	0.000016	0.000015	0.000020
0.000015	0.000013	0.000065	0.000017	0.000024	0.000019
0.000019	0.000016	0.000017	0.000071	0.000030	0.000025
0.000026	0.000015	0.000024	0.000030	0.000069	0.000032
0.000022	0.000020	0.000019	0.000025	0.000032	0.000085];

Table 3: Optimal allotment of six-unit generators by CSO technique

No.	*Demand*	p_1	p_2	p_3	p_4	p_5	p_5	*Loss*	*Total*	*Cost*
1	585	23.87	1.09	96.67	101.58	201.25	174.19	13.67	598.67	31377.33
2	600	24.24	12.40	100.35	98.66	202.39	187.56	14.46	614.46	32087.79
3	700	28.36	8.01	119.55	118.97	231.25	213.31	19.48	719.48	36911.74
4	800	32.58	14.48	141.54	136.04	257.66	243.00	25.33	825.33	41896.70
5	1000	40.83	29.33	185.09	171.10	307.90	305.18	39.46	1039.46	52361.97
6	1200	87.08	61.51	213.75	207.79	352.59	332.22	54.97	1254.97	63809.66

Table 4: Evaluation of price in diverse methods in solving six-unit organization of 600 mega Watts

No.	*CSO*	*Lambda iteration*	*Quadratic programming*	*GA*	*PSO*
p_1	24.24	23.86	23.90	22.8	23.8
p_2	12.40	10	10	10	10.0
p_3	100.35	95.64	95.63	103.3	95.7
p_4	98.66	100.07	100.70	98.9	100
p_5	202.39	202.83	202.82	194.23	202.6
p_6	187.56	181.19	182.02	187.5	181.2
Total	614.46	614.23	615.07	616.73	614.3
Loss	14.46	14.23	15.07	14.2	14.24
Cost	32087.79	32094.72	32096.58	32098.6	32091.68

Table 5: Evaluation of price in diverse methods in solving six-unit organization of 700 mega Watts

No.	*CSO*	*Lambda iteration*	*Quadratic programming*	*GA*	*PSO*
p_1	28.36	28.29	28.33	29.09	28.2
p_2	8.01	10	10	10	10.0
p_3	119.55	118.96	118.95	116.64	118.53
p_4	118.97	118.67	118.67	123.43	118.53
p_5	231.25	230.76	230.75	226.4	230.2
p_6	213.31	212.74	212.80	213.7	214.16
Total	719.48	719.43	719.50	719.23	719.62
Loss	19.48	19.43	19.50	19.4	19.4
Cost	36911.74	36912.20	36914.01	36913.7	36912.22

Table 6: Evaluation of price in diverse methods in solving six-unit organization of 800 mega Watts

No.	*CSO*	*Lambda iteration*	*Quadratic programming*	*GA*	*PSO*
p_1	32.58	32.58	32.63	32.5	31.95
p_2	14.48	14.48	14.48	12.4	10.8
p_3	141.54	141.54	141.54	140.51	153.2
p_4	136.04	136.04	136.04	136.2	151.8
p_5	257.66	257.66	257.65	258.28	247.3
p_6	243.00	243.00	243.00	245.3	229.69
Total	825.33	825.33	825.34	825.19	824.74
Loss	25.33	25.76	25.34	25.44	24.95
Cost	41896.70	41896.70	41898.45	41925.28	41896.2

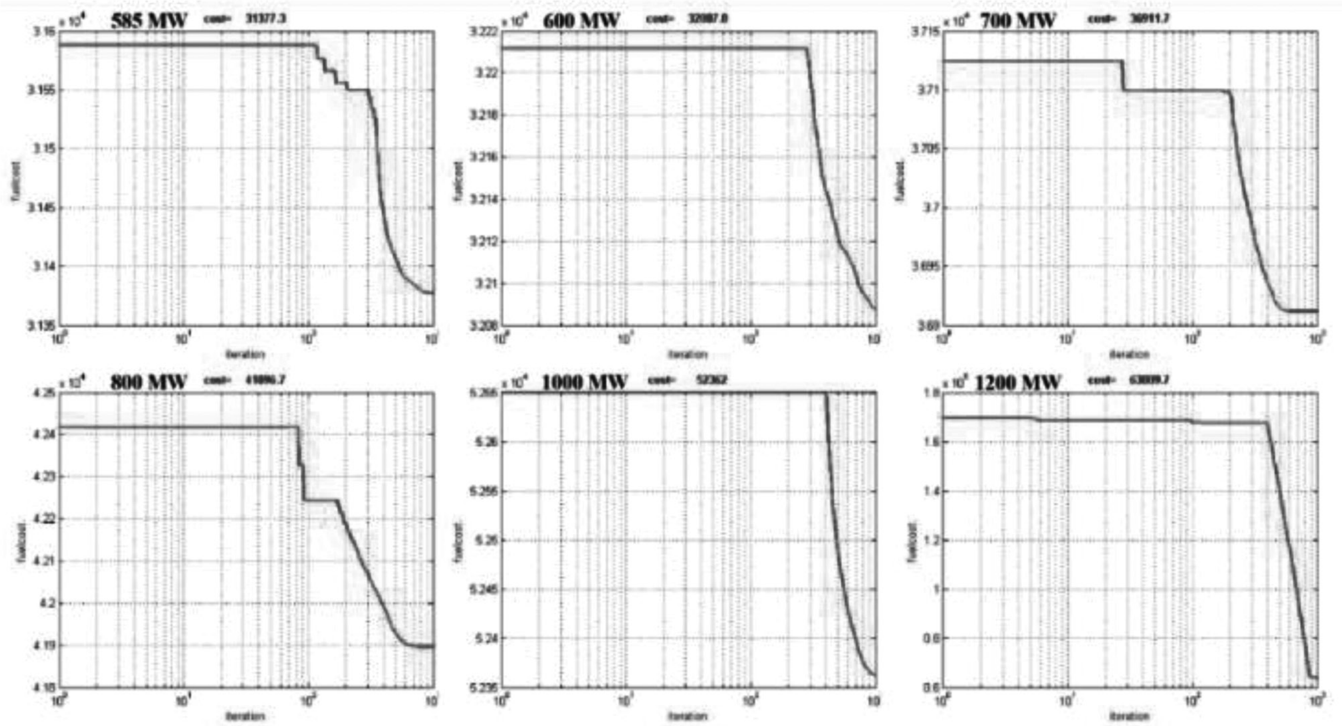

Figure 3: Convergence graph of CSO technique for 30 bus with six generating systems, power demand of 585 mega Watts, 600 mega Watts, 700 mega Watts, 800 mega Watts, 1000 mega Watts and 1200 mega Watts.

convergence features of the CSO algorithm for power demand of 585 mega Watts, 600 mega Watts, 700 mega Watts, 800 mega Watts, 1000 mega Watts and 1200 mega Watts. It is evidently observed from the figures that the CSO algorithm convergences proficiently which reflects the effectiveness of CSO in handling the load dispatch problem. Henceforth, the dominance of the CSO algorithm is guaranteed.

Conclusion

Here, the CSO method is engaged to solve the load dispatch problem for six-unit system. The CSO technique employed uses a pairwise competitive mechanism for faster convergence. The CSO algorithm displayed greater characteristics comprising of better quality solution, and steady convergence features. The CSO method, alongside with other optimization techniques like PSO, GA, lambda iteration and quadratic programming are verified on the load dispatch problem of six system; along with the nonlinear features of the generators are considered. The solution is very much closed to the solution of the traditional methods but promises to provide enhanced solution in the case of system with complex order. The plotted convergence graphs of the projected method for solving the six-unit generating system shows the improving results with the increase in system complexity. Hence, advanced systems can be solved in considerably lesser time than the traditional methods.

Acknowledgements

The authors are very much thankful for the support by TEQIP-III, NIT Silchar, Assam, India.

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